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Comparative Study of Morphological, Correlation, Hybrid and DCSFPSS based Morphological & Tribrid Algorithms for GFDD

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Abstract— **This paper proposes comparative study of two basic approaches such as Morphological Approach (MA) and Correlation Approach (CA) and three modified algorithms over the basic approaches for detection of micronatured defects occurring in plain weave fabrics. A Hybrid of CA followed by MA was developed and has shown to overcome the drawbacks of the basic methods. As automation of MA using DC Suppressed Fourier Power Spectrum Sum (DCSFPSS), DCSFPSSMA could not yield improvement in Overall Detection Accuracy (ODA) for micronatured defects, automation of modified Hybrid Approach (HA) was proposed leading to the development of Tribrid Approach (TA). Modified Hybrid approach involves cascade operation of CA and MA both automated using DCSFPSS. Texture periodicity of defect free fabric was obtained using DCSFPSS which was extended for the design and extraction of defect independent template for CA and for the design of the size of structuring element for morphological filtering process. Overall Detection Accuracy was used by adopting simple binary based defect search algorithm as the last step in the experimentation to detect the defects. Overall Detection Accuracy was found to be ~100%/97.41%/ 98.7 % for 247 samples of warp break defect/ double pick/ normal samples and 96.1% /99% for 205 thick place defect samples/normal samples belonging to two different plain grey fabric classes. Robustness of the performance of TA scheme was tested by comparing TA with two traditional algorithms viz., CA and MA and our previously proposed hybrid algorithm and DCSFPSSMA. This TA algorithm outperformed when compared to CA-only, MA-only, HA and DCSFPSSMA by yielding an overall ODA of more than 98% for the defect and defect free samples of different fabric classes. Secondly, the recognition of defect area less than 1 mm^2 which has not been reported in the literature yet, was possible using this algorithm. We propose to use this method as a means to grade the grey fabric similar to the standard fabric grading system.**

Index Terms— **DCSFPSS, Defect Independent Template, Correlation, Morphological, Periodicity, Tribrid Approach.**

I. Introduction

In process quality check plays a vital role in all the production units. Inspection of fabric for its quality is the last step in weaving process which is based on defect types size and their frequency. Fabric surface is characterized by regular textural features. It is a well known fact that, textural features can be quantified very well by digital image processing techniques such as Fourier transform, correlation and morphological approach. Hence occurrence of any fabric defect can be monitored by state-of-the-art methods using image processing. The proposed novel method is culmination of the image processing algorithms like Fourier transform, correlation and morphological approach. Numerous approaches have been proposed to address the problem of detecting defects in woven fabrics using Correlation Approach (CA) and Morphological Approach (MA). Bodnarova et al. [1], [2], [3] have used the correlation coefficient from multiple templates for defect declaration and have achieved correlation sensitivity of 95% for fifteen defective fabric images with five different defects. We have shown that, CA can support the detection of variety of microstructure defects of varying size for plain and twill grey fabrics [4]. Various approaches have been proposed by researchers [5]-[9] to address the problem of detecting defects in woven fabrics using spatial domain morphological filtering assisted by different methods for selection of Structuring Element (SE). Their experimental results on MA indicate the suitability of MA for fabric defect detection with no obvious improvement over other available approaches [7], have reported a detection rate of 60% in [6] and 97% in [8]. Though correlation technique can detect variety of defects, its dependency on the right defect template, template size, thresholding and false detection of normal region as defective [4] need further attention.

To overcome these, Hybrid Approach (HA) of combining CA followed by MA approach was proposed by us which showed considerable reduction of False Alarm Rate (FAR) i.e. normal being detected as defective and vice versa [10]. However it suffers from the drawback of trial and error method needed for selection of defect template for CA and selection of size of SE for MA. Also CA demands different templates for different defects with a need for optimal thresholding. These issues drove the authors to design defect independent template and design of size of structuring element based on texture periodicity.

It was shown that, Fourier transform and Fourier Power Spectrum (FPS) is useful in finding fabric structure [11], [12] however we realized that, FPS needs further enhancement when fabric structure made of fine yarn count is to be explored for its texture periodicity [13]. In this paper, it was

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shown that the periodicity and thread count of fabric texture can be determined using DC Suppressed Fourier Power Spectrum Sum (DCSFPSS) approach. This DCSFPSS developed in [13] was extended for Grey Fabric Defect Detection (GFDD) which performed well for twill fabric [14] but was not satisfactory for plain fabric. This motivated us to propose a novel Tribrid Approach (TA) method wherein HA was not only modified but also automated using DCSFPSS for design of template for CA and SE for MA. Modified HA uses defect independent template for correlation followed by automated MA method. Proposed TA method which incorporates the advantages of both methods by cascading CA and MA doubles the surety of defect detection and thereby reduces FAR. Therefore DCSFPSS based modified Hybrid (CA+MA) approach coined by as tribrid approach not cited in literature so far was experimented for plain weave GFDD. The experimental details, results and comparative study of CA-only, MA-only, HA, DCSFPSSMA and proposed TA algorithms are discussed further.

II. Therotical Background

This work is based on the idea of applying the texture periodicity to assist CA and MA as a new method for defect detection of patterned texture. Hence texture periodicity is used to select the template for correlation. Then statistical method is used for selection of thresholding automatically. This is followed by extension of DCSFPSS for MA for texture inspection. The theoretical background and considerations for selecting appropriate threshold automatically are presented in the following section.

A. Fabric Patterns and Plain Weave Fabric Defects

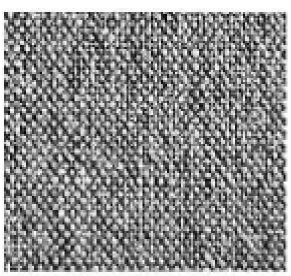

Figure 1. Plain weave normal sample

Woven fabrics is composed of longitudinal or warp threads (ends) and transverse or weft threads (picks), interlaced with one another according to the class of structure and form of design. In simple plain weave pattern, the ends and the picks intersect at right angles and the order of interlacing causes orthogonal intersecting lines to be formed in the cloth as shown in Fig.1. Any weave repeats after a definite number of ends and picks. Generally only one weave Repeat Unit (RU) is of importance [15]. The kind of defects considered for this study are the plain weave micronatured defects such as thick place, loose-weft, double pick and warp break of varying size and magnitudes. Thick place occur due to the yarn uniformity variation by more than 50% of the normal whereas loose-weft is a single filling yarn under insufficient tension and double pick is a defect that occur due to unintentional weaving of two weft wise threads [16], [17].

B. DCSFPSS Theory

Fourier Transform is ideally suited for describing the directionality of periodic or almost periodic 2-D patterns in an image. It can distinguish the global texture pattern easily as concentrations of high energy bursts in the spectrum which is generally quite difficult to detect with spatial methods because of local nature of these techniques. Also Fourier transform has the desirable properties such as noise immunity, translation invariance and the optimal characterization of periodic features. The directionality and periodicity property exhibited by Fourier transform is further enhanced by the Fourier Power Spectrum (FPS) [14], [19] which is essential while determining periodicity for textures of material like fabric made up of fine yarn. The FPS, $P(u, v)$ is equal to the sum of square of the magnitudes of real, $F_R(u, v)$ and imaginary part, $F_I(u, v)$ of Fourier transform and is given by,

$$P(u,v) = F_R^2(u,v) + F_I^2(u,v) \qquad (1)$$

The Fourier power spectrum of a 2-D image, $f(x,y)$ can also be obtained by multiplying Fourier transform of the image by its complex conjugate and is given as below [18].

$$P(u,v) = F(u,v) \times F^*(u,v) \qquad (2)$$

Ignoring the average brightness (DC) of the image to enhance texture features, the sums of the DCSFPS in u and v directions viz., marginals (DCSFPSS) is computed from their corresponding DCSFPSS as given below.

$$P_u(u,v) = \sum_u P_v(u,v) \qquad (3)$$

$$P_v(u,v) = \sum_v P_u(u,v). \qquad (4)$$

Periodicity of the fabric pattern is obtained by detecting prominent peaks and their location from the marginals of defect free plain weave fabric. This can be further used to obtain the Number of Repeating Elements (NRE) in the fabric image and in turn can be used for finding the size of the structuring element for morphological operations. The work related with the next section deals with procedure and results of experiments performed using CA, MA and previously developed HA [10] by the authors. It also highlights the drawbacks and the necessity of new approach.

Table I. Details of Plain Weave Samples

Class	Fabric Specifications	Type of Defect	Number of Defects
S1	$\frac{132 \times 132}{60 \times 60}$	Normal	91
		Warp break	98
		Double Pick	78
S2	$\frac{144 \times 144}{80 \times 80}$	Normal	105
		Thick Place	100
S3	$\frac{124 \times 64}{30^s \times 150\ D}$	Normal	75
		Thick Place	50
		Double Pick	50

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III. Image Acquisition

To carry out the fabric fault detection, both defective and defect free (normal) samples of plain weave, generally used for suiting, were collected from the textile industry. Motorized Micro-stereoscope with optical magnification was used as an imaging device. The images of the fabric samples were taken after standardizing the Motorised Zeiss Sterio microscope for magnification of 12x, focus of 19 and depth of -1.5mm. The resolution of the image obtained was 1280x1040 pixels which was then reduced to 512x512 pixels using Microsoft Digital image editor. The image data base of plain grey fabric of three classes viz., S_1 and S_2 and S_3 is as given in Table I.

IV. CA, MA, HA, DCSFPSSMA and TA

To arrive at an appropriate method for GFDD, two traditional approaches viz., CA [4] and MA were verified. Based on these results and the intuition developed, a modified method viz., hybrid approach [10] which consisted of CA followed by MA was developed and tested. Promising results of DCSFPSS for determination of periodicity and thread count [13] led to the development of modified MA viz., DCSFPSSMA (This uses automation of size of SE for MA) for plain weave GFDD similar to [14]. But failure of DCSFPSSMA and encouraging results of HA prompted us to develop modified HA viz., Tribrid Approach (TA) for plain weave GFDD. It uses automated CA that employs defect independent fabric specific template extracted from normal sample using DCSFPSS followed by automated DCSFPSSMA. Thus complete automation introduced in modified HA led to the development of TA. The brief details of CA,MA, HA, DCSFPSSMA experimentation for plain weave GFDD is presented first followed by proposed TA experimentation. The details of the experimentation and the results thereof are presented further.

A. Correlation Approach

In this method after converting fabric RGB image to gray image, it was subjected to the adaptive histogram equalization for contrast adjustment. After manually choosing the proper defect template from histogram adjusted image, it was sized equal to the size of the image to make correlation computation more efficient. In CA algorithm, the correlation of the template image with the original image was computed by rotating the template image by 180^0 and then using the FFT based convolution technique described by fast convolution. The Correlation Coefficients (CC) were then thresholded using the simple statistics of the coefficients such as mean and maximum value to retain the defect region.

1) CA Experimentation and Results: For plain weave GFDD using CA, four different kinds of plain weave defects including defects of subtle nature were considered as shown in Fig.2. With reference to Fig.2., column C_1 depicts images of on warp break (S_1), double pick (S_3), thick-place (S_2) and loose-weft (S_3) defects respectively from top to bottom. The defect templates corresponding to these defects are as shown in column C_2 while the result of correlation convolution of the defect images with their respective defect template are shown in column C_3. The defect areas for each kind of defect obtained after thresholding of correlation coefficients is as shown in column C_4 of Fig.2. The threshold which best approximates the actual defect location and area was obtained after a pool of directed experiments and was used further for experimentation on other samples with the similar kind of defects.

Following are the observations on CA referring to Fig.2.

- There is false identification due to Normal Region being Identified as Defective (NRID) at several places of an image. This is quite obvious in all result images in column C_4 of Fig.2., indicating that the results are not very satisfactory.
- Correlation approach needs different template for each kind of defect considered. The defect and its area identified were dependent on the kind and size of the defect template which makes GFDD a tedious and time consuming process.

These drawbacks motivated us to test most commonly used Morphological Approach for GFDD of plain weave pattern.

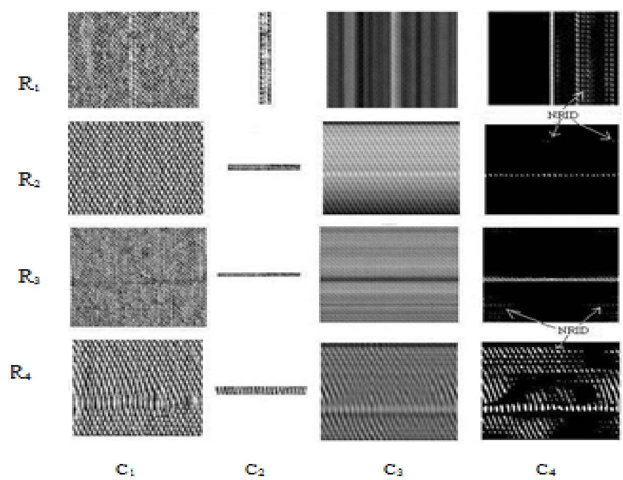

Figure.2. Results of Correlation Approach on Plain fabric Defect images

B.MA Method

The experimental procedure using MA only was followed on benchmarking plain weave fabric defects such as warp-break (S_1), thick place(S_3) shown (columns C_1/C_2 in Fig.3.A/ Fig.3.B) and double pick(S_2) (column C_3 in Fig.3.B.) Two sets of observations were taken on the histogram equalized image shown in row R_1 of Fig.3.A and Fig.3.B. respectively.

1) MA Experimentation and Results: The sequence of Morphological Operations (MO)s followed to obtain two sets of results shown in Fig.3.A and Fig.3.B are as depicted in Table II. The first set consists of all morphological operations with image filling (imfill) operation while the second set corresponds to all steps except image filling operation. Following observations are made for the MA application for normal and defective plain grey fabric samples;

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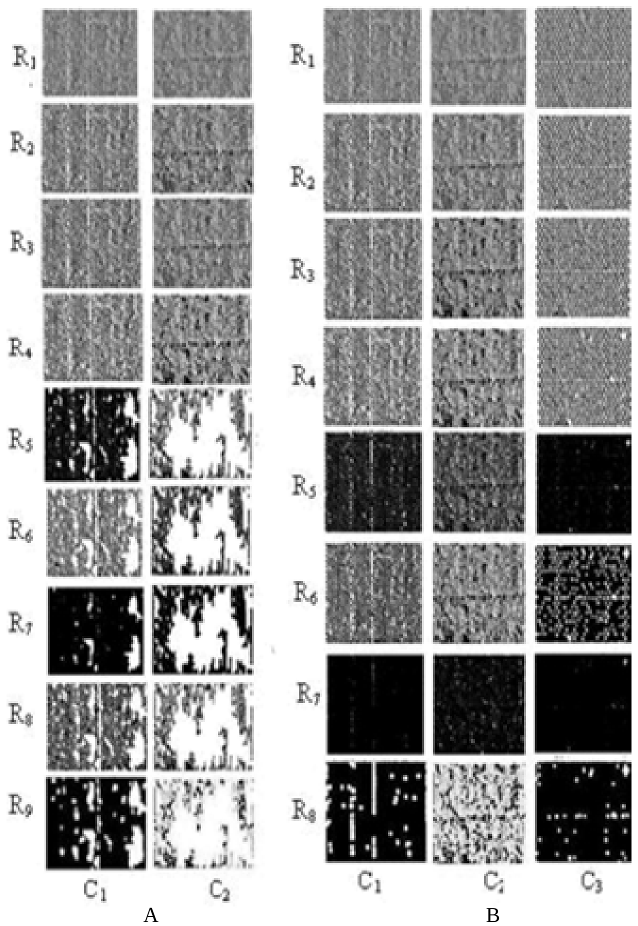

Figure 3. Results of MA on Plain Fabric Defect Image Samples. A. With image filling operation added in the sequence. B. Without image filling operation

TABLE II. RESULTS OF MA APPLIED ON DEFECT SAMPLES
FIG. A. WITH IMAGE FILLING OPERATION,
FIG. B. WITHOUT IMAGE FILLING OPERATION

Fig.A.	Fig.B	MA Operations
R_1	R_1	Thresholded Gray image
R_2	R_2	Opening Image after thresholding using disk SE
R_3	R_3	Closing image of row R_2
R_4	-	Filling small holes in row R_3
R_5	R_4	Erosion of image in row R_4/R_3 with SE eye
R_6	R_5	Dilation of images in row R_5/R_4 with SE eye
R_7	R_6	Erosion of image in row R_6/R_5 with SE rectangle
R_8	R_7	Dilation of images in row R_7/R_6 with SE rectangle
R_9	R_8	ROI detection of images in row R_8/R_7

- From Fig.3.A for warp break and thick place defect, it is clear that, MO with imfill operation fails to detect region of interest (ROI) for plain weave pattern. This is due to the fact that, plain shirting fabric being made out of very fine yarn count makes the repeat unit of weave pattern very small in area and makes texture to become more dense in nature.
- The image filling operation on this removes texture information more than expected causing too high degradation of ROI (Refer row images from R_5 to R_9 of Fig.3.A.)
- From Fig.3.B it is seen that, though elimination of imfill operation from MO sequence results in improvement in detection of ROI compared to Fig.3.A, it fails to give satisfactory results (Refer row R_8 of Fig.3.B).
- Comparing images in row R_8 of Fig.3.B for the warp break, thick-place and double pick, it is seen that detection of ROI for warp break is better than that for double pick while it is the worst for thick-place samples.

The above observations of MA on plain weave defects suggest that, MO operation fails for plain weave defects in detection of normal region and defect region accurately. Image filling operation does not work effectively for noise removal. This is attributed to the fact that the noise addition due to protruding yarn for defective region of plain weave fabric made of fine count is almost feeble even in the defect region. Accordingly the steps of MA need modification to achieve better results for detection of ROI and hence to achieve good Overall Detection Accuracy (ODA) for both normal and defective samples. Looking at the poor performance of MA, we experimented hybrid approach viz., HA which combines the benefits of CA and MA for plain weave GFDD.

C. Hybrid Approach

From careful observation of the results on GFDD on plain weave, it seen that both, MA and CA can identify the defect region i.e. ROI when applied independently, but result in large False Alarm Rate (FAR) for normal region. Thus there is a probability of the fabric normal region getting identified as the defective as reported in [1], [2] and also verified in [4] for micro natured defects. To overcome this drawback and to utilize the advantages of correlation property of CA and filtering property of MA to detect ROI, the next drive in this research was a hybrid approach for GFDD.

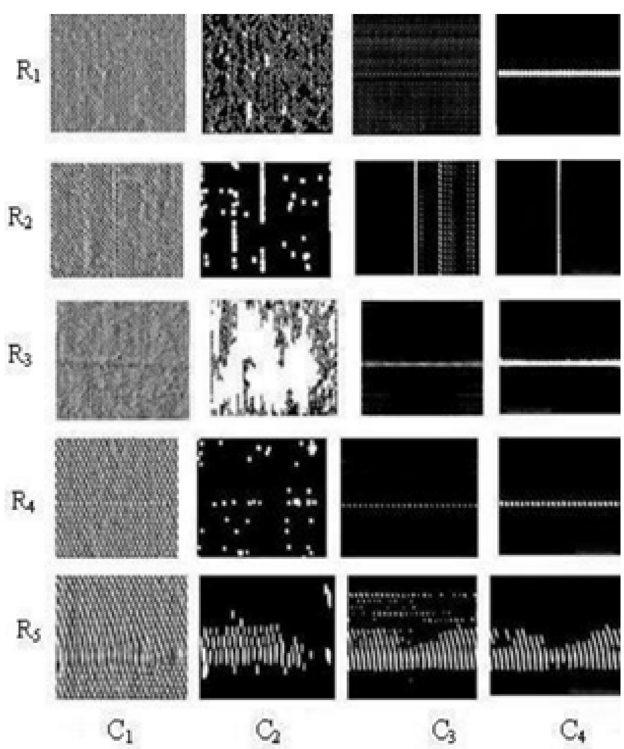

Figure 4. Result Images Showing Detect Region Detected by MA, CA and HA Algorithms

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In this direction hybrid algorithm using combination of CA followed by MA was developed and experimented on plain weave defects. The algorithm and results of this HA on fabric plain weave are presented below.

1) HA Experimentation: In HA, the procedure as explained in Section IV.A.1 was adopted for CA part of HA using defect dependent templates for plain weave GFDD. It is necessary to keep the threshold at optimal value to extract ROI from all similar kind of defect images of one fabric class. This was to avoid any defect region being missed. But this is found to increase FAR for normal region. Hence filtering property of MA was used on the thresholded correlation coefficient images to retain only defect region. Suitable area of SE for opening operation of MO was selected after directed experiments to retain the seed of the pattern which was subsequently closed by the same SE. The grey fabric consists of protruding yarn resulting in the form of small pepper noise which needs (which gets exaggerated in fault region) to be removed by filling operation. The next steps followed for extracting ROI were similar to steps used in MA only. The implementation results of this hybrid approach are discussed in the following subsection.

2) HA Observations and Results: For experimentation on HA, the defects that were used for GFDD using CA were considered for study as per Table III. In Fig. 4, the column C_1 represents the defect gray image, column C_2 depicts the results of MA, while columns C_3 depicts the results of CA approach and C_4 depicts the results of hybrid CA and MA approach.

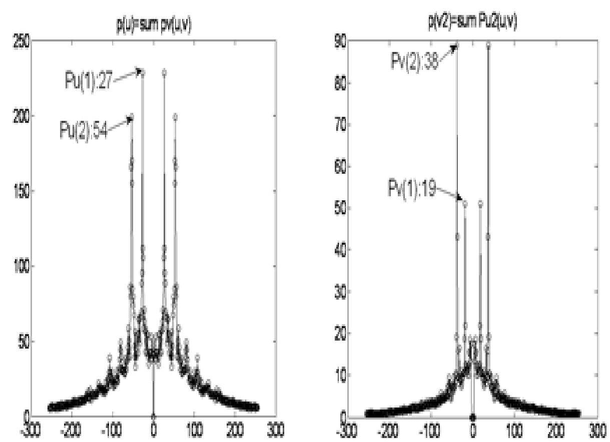
TABLE III. DETAILS OF MA, CA AND HA OPERATION

Weave Type	Defect name (Row wise)	Image/Operation (Column wise)
Plain	R_1: S_2 -Double pick	C_1:Gray Image
	R_2:S_1-Warp break	C_2:Result of MA
	R_3:S_3-Thick place	C_3: Result of CA
	R_4:S_2-Looseweft	C_4:Result of HA
	R_5:S_3-Double pick	

Focusing the discussion on column C_2 and C_3 on detected ROI for all plain weave defects, it is seen that, neither MA-only nor CA-only can independently identify the defective region correctly. Normal region is identified as defect at several places indicating more FAR. This is for the reasons that MA cannot catch purely ROI for plain weave defects when count of the fabric becomes fine. Also in CA as stated earlier, defect area identification is mainly dependent on the thresholding value of correlation coefficients. The threshold that could best detect the defect region was chosen and used for further experimentation to avoid any chance of defect free region being detected as defect region. The problem of NRID i.e. identifying the normal region as defective at several places is almost eliminated by the successive CA followed by MA (Refer to result images in column C_4 of Fig.4).

Similar results were observed for other kind of defects of plain weave defect samples. It is seen from column C_4 that, though HA performs better than CA-only or MA-only but it lacks automation. However, it uses defect dependent template demanding different template for each kind of defect. Thus there is no unique template which makes the process tedious and cumbersome. These observations on HA led to the development of modified HA where, defect independent template was extracted from normal sample for CA. Based on these results and the intuition developed, a modified method viz., hybrid approach [10] which consisted of CA followed by MA was developed and tested. Promising results of DCSFPSS for determination of periodicity and thread count [13] led to the development of modified MA viz., DCSFPSSMA (uses automation of size of SE for MA) for plain weave GFDD similar to [14]. But failure of DCSFPSSMA and encouraging results of HA prompted to develop automation in modified HA viz., Tribrid Approach (TA) for plain weave GFDD. It uses automated CA that employs defect independent template extracted from normal sample using DCSFPSS followed by automated DCSFPSSMA. Thus complete automation introduced in modified HA led to the development of TA.

The brief details of DCSFPSSMA experimentation for plain weave GFDD is presented first. This is followed by the theory on TA and experimentation results further.



a b

Figure 5. DCSFPSS application on normal plain weave sample in
a. u direction b. v direction

D. DCSFPSSMA Approach

For this part of experimentation, size of structuring element for morphological operations on plain weave fabric texture image was designed and extracted automatically from DCSFPSS similar to [13]. Hence design procedure for computing size of structuring element and brief experimentation of DCSFPSSMA is explained next.

Since fabric texture is periodic in nature and fabric is made up of repeat units having Repeating Elements (RE), the periodicity information would be an obvious choice for design of SE for morphological operations that should mimic repeat element of fabric texture. Structural element needed for morphological operation was designed from DCSFPSS, $P(u,v)$ i.e. marginals plot of several normal plain weave images [13]. Marginal plot of benchmark normal plain weave

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sample has only two dominant peaks as shown in Fig.4. Significant peaks like *Pu*(1)/*Pu*(2) units from marginal center, *Pu*(0) in u direction and *Pv*(1)/*Pv*(2) units from marginal center Pv(0), in v direction are clearly seen in the plot of Fig. 5.a and Fig. 5.b respectively and these correspond to periodicity/ thread count in warp and weft direction of fabric respectively. Hence, it follows that, Number of Repeat Elements (*NRE)* for the fabric image is product of texture periodicity in u direction and thread count in v direction as given in (3) and the area covered by one repeat element (*AE*) is as given by (4).

$$NRE = Pv(2) \times Pu(1) \cdot \tag{3}$$

$$AE = \frac{P_L \times P_W}{NRE}. \tag{4}$$

where, P_L and P_W are the number of pixels in lengthwise and widthwise direction of image. Size of SE needed for MA operation was obtained from (4).

E. Observations on DCSFPSSMA

It was observed that, GFDD experimentation using DCSFPSSMA method produced the Overall Detection Accuracy (ODA) results similar to MA-only (refer Table 5) since it incorporates only automation of SE. Hence to improve upon this, TA method, that modifies and automates HA was developed and tested. Accordingly additional design for automation of *defect independent normal template* using DCSFPSS and selection of suitable thresholding of CCs for CA part of TA, the details of TA experimentation are explained next.

V. Novel Tribrid Approach

Since the periodicity of fabric texture and number of repeating elements out of which the fabric is made are related, the intuition then developed was that, periodicity information should be an obvious choice also for design of defect independent template for CA. It is quite evident that, repeat elements of repeat unit of fabric texture are related to periodicity. Thus the objective of TA was threefold i.e. 1) automating the selection of defect independent normal templates, 2) choosing appropriate threshold for thresholding of Correlation Coefficient (CC) s and 3) designing suitable size of SE for MA. For the first and third objectives, the designs were assisted by novel DCSFPSS approach whereas second objective follows statistical approach on CCs. Analytical treatment followed to meet these objectives is explained further in detail.

A. Design of Defect Independent Template for CA

Auto selection of width of defect independent normal template (*TW*), warp-wise normal template, (NT_{warp}) as well as weft-wise normal template, (NT_{weft}) for an image (I_m) are computed using the following equations in MATLAB referring to Fig.5.

$$TW = \frac{P_W}{Pv(2)}. \tag{5}$$

$$NT_{warp} = I_m(1:512, C_y + T_W). \tag{6}$$

$$NT_{weft} = I_m(C_x : C_x + Pu(1), 1:512). \tag{7}$$

Here value C_x, and C_y are constants which are any appropriate starting value of x and y coordinate of normal image.

B. Choice of Thresholding

Appropriate choice of threshold for correlation image which is pivotal in defect finding is always critical. The threshold (T) is based on mean, (μ) and standard deviation, (σ) of correlation coefficients. Both parameters are obtained from correlation of fabric images with normal template and a constant(c). The threshold value, (T) depends upon the constant c, which is specific to a fabric class. Further actual T is computed by averaging the value of T obtained for N number of normal images. The threshold that could detect normal samples with minimal false alarm rate was chosen for defect finding. The threshold is obtained by,

$$T = \frac{1}{N}\sum_{i=1}^{N} \mu + c \times \sigma \tag{8}$$

These design equations based on novel DCSFPSS met the first and third objectives. The size of structuring element needed for MA analysis of TA was obtained using (3) and (4). Two different normal templates needed for CA operation were computed from DCSFPSS using (6) and (7). These are helpful to correlate and find microstructure defects that might be in warp or weft direction. A suitable threshold was computed using (8) for thresholding CCs. The steps followed in TA are as per flow chart of Fig.6.

C Flowchart for TA Experimentation

The flowchart for TA experimentation is as shown in Fig.6. Periodicity was first obtained using DCSFPSS to arrive at selection of normal template of size equal to one repeat element of the weaving pattern in both warp and weft direction. Correlation of fabric image and the normal warp-wise template was computed and applied on the test samples. Decision about the sample as belonging to normal or defect was carried out by subjecting test image to CA, then to MA without image filling, subsequently to Defect Search Algorithm (DSA). Threshold based on statistics of CCs was applied to retain the approximate defect region. Further this thresholded image was subjected to morphological erosion followed by dilation only once unlike two times used in the DCSFPSSMA [14]. This is due to the fact that already identified approximate defect region by CA is in binary form and it needs further filtering by subsequent MA operation for identifying defect region correctly.

The defect Region of Interest was identified as defective, only if the size of repeat element, AE was outside the size limit given by the relation, 0.8xAE<ROI<1.25xAE as per textile norms. For the sample which failed DSA test, the above procedure was repeated again with weft-wise normal template to find the defect if present in weft-wise direction. The sample was declared as normal in case of failure of DSA test conducted otherwise the thresholded CCs of this sample were re-subjected to DSA with MA consisting of image filling

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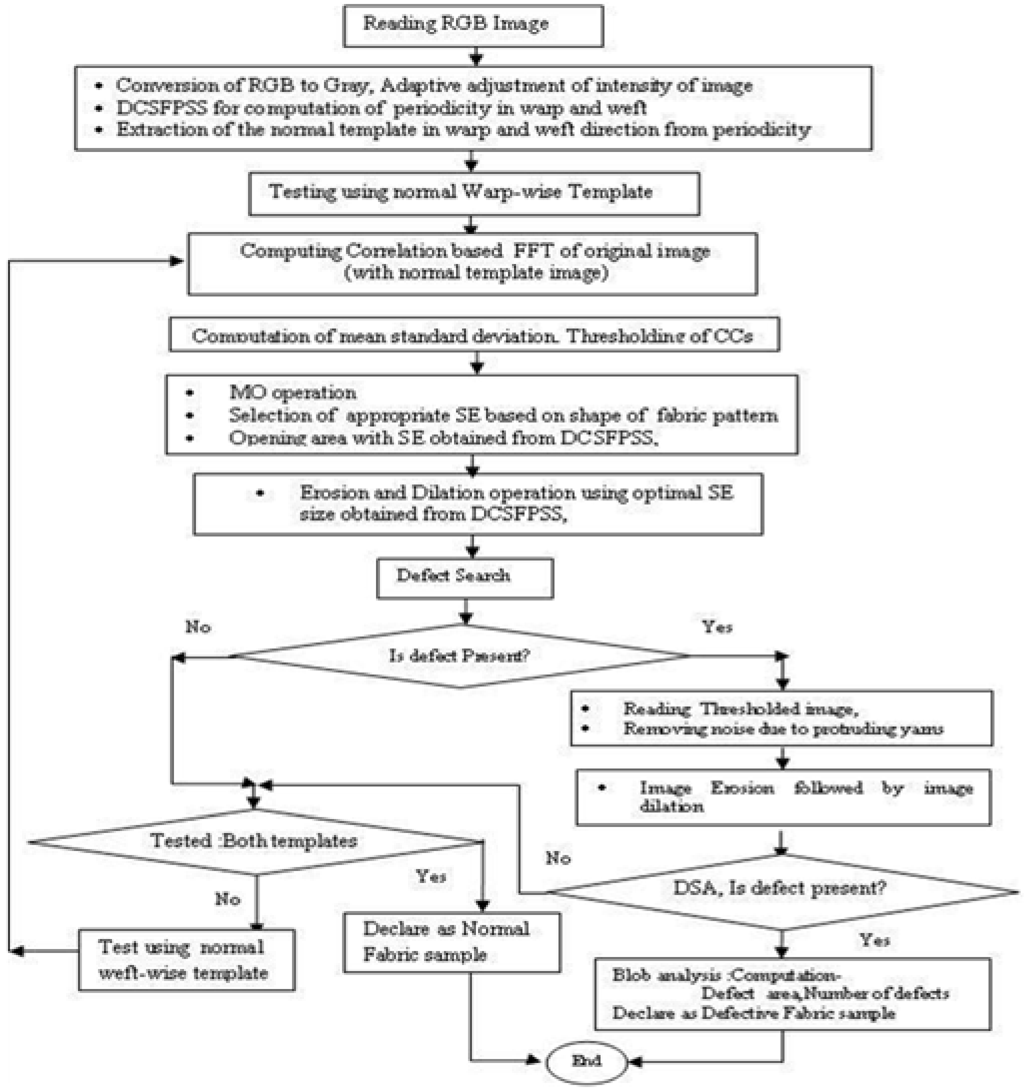

Figure 6. Flow chart of TA for plain Weave GFDD

operation. This operation to remove noise due to protruding yarn was followed by erosion and dilation. The blob analysis was then performed to obtain the defect area and DSA was applied on the blob analyzed image to differentiate defect and defect free samples.

D. Observation and Results

The results for TA applied on various plain weave defects are as in Fig. 7. In all the cases of this analysis, the defect regions are indicated by the bright region. The results of the application of TA are as shown in columns C_1, C_2, C_3 and C_4 of Fig. 7 that correspond to the normal, warp break (S_1), thick-place (S_2) and double pick (S_3) defects respectively. Correlated images obtained after convolving defect free templates in row R_2 with gray images in row R_1 are shown respectively in row R_3 of Fig.7. Black and white images in row R_4 were obtained after subjecting images in R_3 to statistical thresholding CCs decided by (8). To obtain optimal value for constant 'c' which is fabric specific and is related with thresholding for a plain weave, preliminary experiment was conducted for different values of threshold and FAR was computed on normal samples. Table IV shows the results of FAR for different values of thresholding for detection of normal samples. It is seen from Table III that, FAR improved considerably with increase in threshold value. The value of threshold that gave minimum FAR was taken for finding 'c' in (8). Similar procedure was conducted for fabric of other specifications.

Simple binary search was adapted with binary one value indicating the true normal sample and binary zero value indicating the true defect sample for finding FAR. The images in row R_5 are images obtained after subjecting the correlated and thresholded images of row R_4 to morphological open and close operations using disk type structuring element. The optimal SE used for this operation was $(1/16)^{th}$ of size of AE obtained from (4) from normal fabric. This helped to retain seed of the pattern. It should be noted that 255x255

Table IV. Optimal Threshold Value for Normal Sample

Fabric Class	Threshold	Number of Samples	ODA %	FAR
S_1 Class Normal	0.92	78	84.5	16.5
	0.94	78	92.4	7.5
	0.96	78	100	0.0

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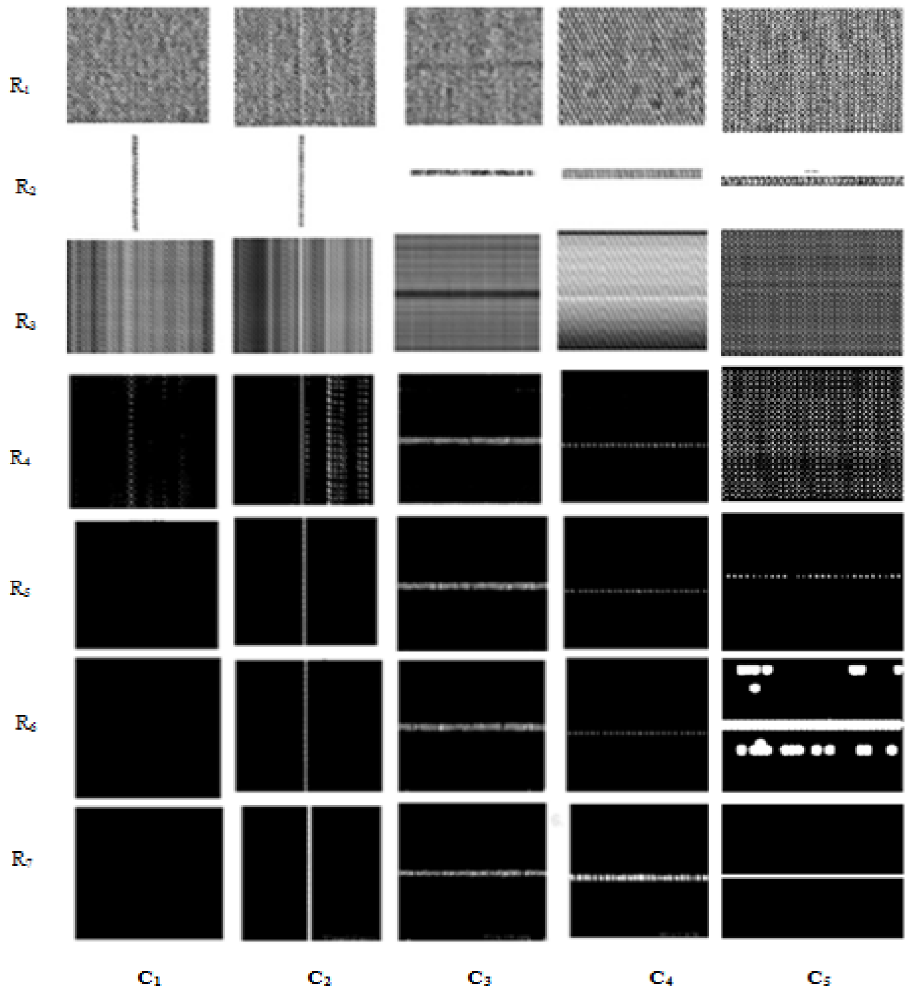

Figure 7. Images of TA Application on Different Class Plain Grey Fabric Defects

pixels correspond to an area of 0.08056 mm^2 of an image. The images after filling operation are depicted in row R_6. The next step for extraction of region of interest i.e. defective region was done using dilation operation using structuring element (disk) of size obtained by halving the value obtained by (4). The results of these operations are depicted in row R_7.

The images in row R_7 were then used for finding defect if exists. As grading of any fabric needs the statistics of defects such as defect area and number of defects in a given area of the fabric, blob analysis was performed on the dilated image in row R_7. This algorithm first locates the region with white pixels using connected component theory and counts the number pixels of each defective region. This was then converted into region area in mm^2 by appropriate conversion factor obtained by imaging system through standardization. Disk type SE i.e. similar to shape of on repeat element of plain weave pattern assisted in extraction of ROI at different stages of morphological operations. The result of this DSA are shown in Table V for warp-break defect samples of class S_1 and thick-place defect of S_3 class with optimal threshold constant 'c' obtained as depicted.

The overall summary of experimentation is as below:

- It is seen from the results in Table IV that, for normal samples of S_1 class fabrics, ODA achieved is 85%, 93% and 100% respectively for different thresholds of 0.92, 0.94 and 0.96. This indicates that appropriate value of threshold is very crucial to get low FAR. It is also found that constant 'c' of thresholding depends on the fabric specification.
- As is clear from Table V, only one step morphological operation for plain weave with disk SE could yield fairly good result, giving ODA of 98.7% with an average false alarm rate of 1.3% especially for normal samples. This is in contrast to two stage MA required to detect the fabric defects in MA.

TABLE V. RESULTS OF TA METHOD FOR PLAIN WEAVE GFDD

Threshold (T)	Defect/ Normal	Number of amples	Detected Samples	ODA In %	FAR in %
$\mu+1.94\sigma$	S_1 –Warp break	78	78	100	0.00
	S1-Double Pick	78	76	97.4	2.56
	S_1-Normal	91	90	98.7	1.3
$\mu+2.8\sigma$	S_3 –Thick-place	105	101	96.1	3.9
	S_3-Normal	100	99	99	1.0

- It is seen from Table V that, DSA reports 98.7% ODA for normal samples whereas 100% /97.43% ODA for warp break/

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double pick faulty samples of the class S_1. Also ODA of 99% was achieved for S_3 class normal samples whereas the same for thick-place defect samples of the S_3 class was found to be 96.1%.

- The row R_7 of Fig.7 show the blob analyzed image sample with warp-break, thick-place and double pick defect with defect area of 0.15, 3.5 and 2.77 mm^2 respectively.
- Fairly good value obtained for ODA indicate appropriateness of the design of template, threshold for CA and design of size of SE used in different steps of MA with selection of type of SE.

This indicates that, the proposed TA method can detect defect with FAR of ~1.3% for normal and also detect the defect with an area less than 1mm^2 which is not reported in the literature yet.

VI. Comparison of CA, HA, DCSFPSSMA and TA

The performance of the proposed TA algorithm was compared with other four algorithms viz., CA[4], MA, HA[10] and DCSFPSSMA(D-MA) using overall detection accuracy as a performance metric on benchmark warp-break defective, double pick and normal samples of S_1 class which is as shown in Table VI. Referring to Table VI, the following points can be noted;

- MA-only algorithm and DCSFPSSMA perform poor for GFDD whereas CA-only approach almost doubles the ODA%.
- Hybrid algorithm improves the ODA to 79%. DCSFPSSMA (D-MA) produces results similar to MA-only approach as it incorporates only automation of size of structuring element for plain weave GFDD.
- The overall detection accuracy of grey fabric detection using TA approach is much higher than any of the other methods for both defective and normal fabric samples.
- FAR% is the lowest in TA method with FAR of 0.0/2.6% for defective warp break/double pick and 1.3% for defect free samples indicating the superiority of TA algorithm.

Table VI. Comparison Results of MA, CA, HA, DCSFPSS-MA and TA

S_1 Class Defect /Normal	Number of Samples	ODA in %				
		MA	CA	HA	*D-MA	TA
Warp-Break	78	28.2	55.1	79.1	28.2	100
Double Pick	78	30.0	58	77.5	30	97.4
Normal	91	25.3	45.9	93.4	25.3	98.7

*D-MA-DCSFPSSMA

All the above points clearly indicated the superiority of the proposed TA algorithm.

VII. Conclusion

This paper has presented the comparative study of CA, MA HA DCSFPSSMA and novel tribrid approach proposed by for GFDD which has resulted into an overall ODA of better than 98%. In TA, DCSFPSS assists automation of a) defect independent normal template for CA along with statistical based thresholding and b) for design of size of SE for morphological operations. The method helps to detect the subtle micro-natured defects with less than 1mm^2 area which we claim as the contribution of our research work. It is found that, TA method out performed amongst all other traditional and modified methods experimented for GFDD of grey plain weave fabric with subtle faults. The problem of FAR for detection of normal samples has drastically improved in TA as needed by GFDD. Designing appropriate normal template for CA and size of SE for MA, both based on novel DCSFPSS approach, modifying HA is the contribution of our research.

Thus TA incorporated modification and provided automation of HA and more importantly it gave improved ODA% for plain weave GFDD. As a future scope of Novel TA method, there is a scope for extending it to other kind of plain weave fabric defects and also for GFDD on other fabric weave patterns such as twill weave fabrics with different defects. More importantly this method can be used to assist the grading of the grey fabric using the statistics such as number of defects detected and area occupied by the defect with relevance to the standard grey fabric grading system to carry out the in-process quality check.

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References

[1] A. Bodnarova, M. Bennamoun, and K.K. Kubik, “Defect Detection in Textile Materials based on Aspects of the HVS”. in Proc. IEEE SMC’98,1998, Conf., San Diego (U.S.), pp. 4423– 4428.

[2] M. Bennamoun and A. Bodnarova, “Automatic Visual Inspection and Flaw Detection in Textile Material: Past, Present and Future”, in Proc. IEEE Conf. SMC 1998, pp. 4340–4343.

[3] A. Brodnarova M.. Bennamoun and K.,K., Kubik., “New Suitability Analysis of Techniques for Flaw Detection in Textiles using Texture Analysis,” Pattern Analysis and Applications 2003: 2000 Springer-verilog London Limited, pp.254–266, 2000.

[4] Jayashree, V., Dr. S. Subbaraman, S. “Correlation Approach for Grey Fabric Defect Detection and Defect Area Measurement,” Proc. National Conference on Emerging Trends in Electronics ncert11, pp.420–425.

[5] Y.F.Zhang and R.R. Bresee.” Fabric Defect Detection and Classification using Image Analysis,” Text. Res.J., vol. 65, pp. 1–9, January 1995.

[6] B. Mallick Goswami, and A.K. Datta, “Detecting Defects in Fabric with Laser-based Morphological Image Processing,” Text. Res. J., vol., 70, pp.758–762, Sep (2000)

[7] Che-Seuing Cho, Byeong-Mock Chung, Member, IEEE, and Moo-Jin Park, “Development of Real Time Vision-based Fabric Inspection System,” IEEE Trans on Industrial Electronics, Vol., 52, No.4, pp.1073–1079, August 2005.

[8] K.L.Mak,, P. Peng, and H.Y.K Lau, “Optimal Morphological Filter Design for fabric Defect Detection,”. IEEE, 0-7803-9484-4/05/ 20, pp.799–804, 2005.

DOI: 01.IJSIP.5.1.1540

[9] K. Jayanta, Chandra and K. Pradipta, Banerjee, Asit, K. Datta, “Morphological Reconstruction Operation for the Detection of Defects in Woven Fabric,” IEEE Region 10 Colloquium and the Third ICIIS, December 8-10, PID763474 (Conference paper Number 491), pp. 1–5, Kharagpur, India, 2008.

[10] V.Jayashree, and Dr.S. Subbaraman “Hybrid Approach using Correlation and Morphological Approaches for GFDD of Plain Weave Pattern,” in Proc. 2012 IEEE Control and System Conference on Graduate Research Colloquim, July 16- 17, UiTM, ICSGRS 2012, vol.I, pp.290–295, Proceeding Books ISBN: 978-1-4673-2034-4 2012IEEE, IEEEXPLORE, Shah ALam, Malaysia, (2012)

[11] S.A.H. Ravandi and K. Toriumi, “Fourier Transform of Plain Weave Fabric Appearance,” Textile Research J., vol., 65, no. 11,pp. 676–683, 1995.

[12] Bugao Xu, “Identifying Fabric Structures with Fast Fourier Transform Techniques,” Textile Res.J., vol. 66(8), pp.496–506, 1996.

[13] V. Jayashree and Dr.S. Subbaraman, “DC Suppressed Fourier Power Spectrum Sum: A means to Determine Periodicity and Thread Count of Fabric,” International Multi Conference of Engineers and Computer Scientists 2009, London, U.K. WCE 2009, July 1 - 3, 2009, vol., I, pp. 441–446, Proceeding Books ISBN (Vol., I II): 978-988-17012-5-1, 978-988-17012-5-0. Lecture Notes in Engineering and Computer Science WCE 2009.

[14] V. Jayashree, and Dr. .S. Subbaraman,” DCSFPSS Assisted Morphological Approach for Grey Fabric Defect Detection and Defect “Area Measurement for Fabric Grading.: Proc. International Symposium on Electronics Design ISED11:Dec 19-21-2011, ISBN 978-0-7695-4570-7, BMS Number CFP1157L-CDR, IEEEXplore, INSPEC pp.290–295, Kochi India , 2011.

[15] Z.J. Grosciki, Construction of Elementary Weaves in Watson’s Textile Design and Color Elementary weaves and Figured Fabrics, Seventh edition, WP, England 2004.

[16] Textile committee, Catalogue on woven fabric defects and visual inspection systems, India, 2009.

[17] Standard Terminology Relating to Fabric Defects, ASTM standard Designation D3990-93, Annual books of ASTM Standards Textiles, Vol. 0702, Section 7, 1997, pp. 205–211.

[18] Maria Petrou and Pedro Garcia Sevilla, Image Processing Dealing with Texture, John Wiley and sons Ltd., England , 2006, pp.132, 260–265.

[19] Bernd Jehne, Practical Handbook on Image Processing for Scientific and Technical Application, CRC, IEEE Press, ISBN-0-8493-1900-5, 2004.

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